Assessing Current & Future Infrastructure Hazards:

Forecasting Integrity using Machine Learning & Advanced Analytics

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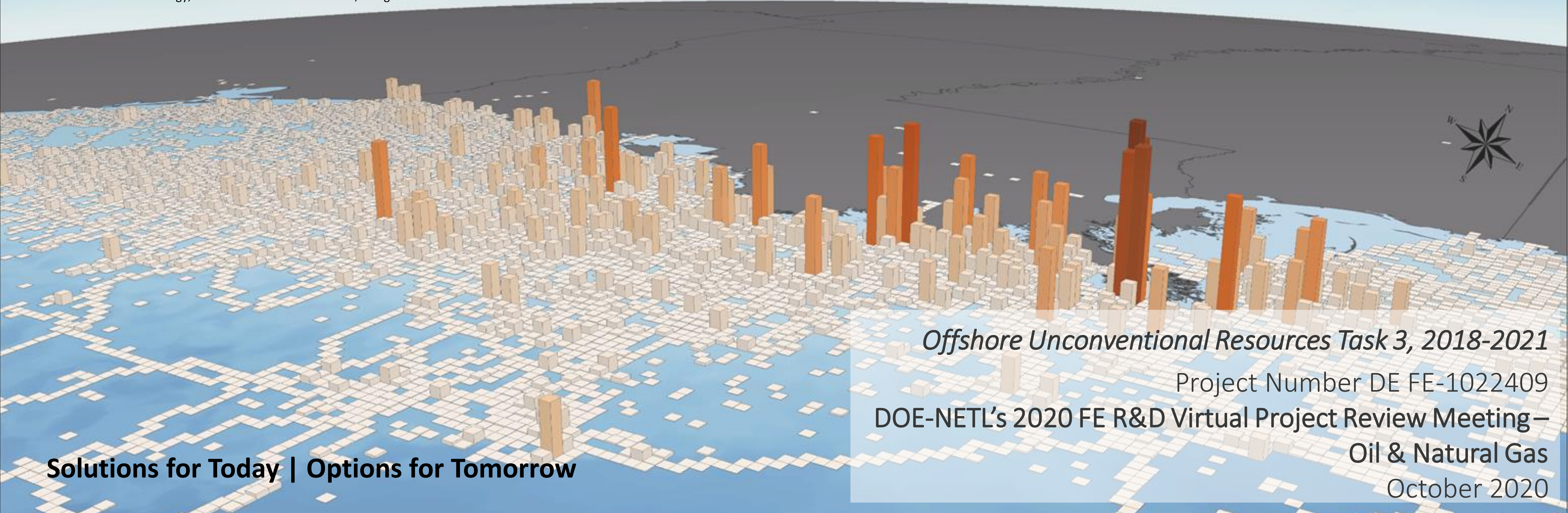


Offshore Unconventional Resources Task 3, 2018-2021

Project Number DE FE-1022409

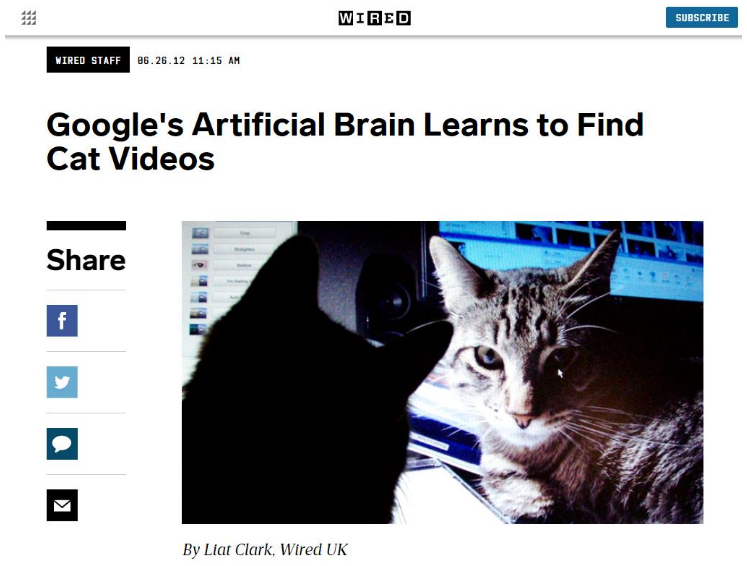
DOE-NETL's 2020 FE R&D Virtual Project Review Meeting – Oil & Natural Gas

October 2020

Solutions for Today | Options for Tomorrow

A few definitions to set the stage…

- **Artificial Intelligence**
  - "Programmed" intelligence
- **Machine Learning**
  - **Supervised ML**, the machine is trained, taught
  - **Unsupervised ML**, the machine learns on it's own (Google's cat video experiment)
- **Big Data**
  - Large volumes, variety, variability, velocity of data
- **Big Data Computing**
  - Computing engineering & systems to handle big data



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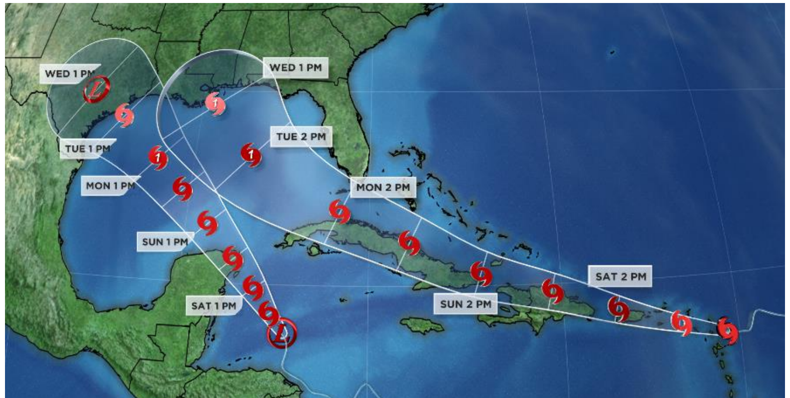
What is the need?

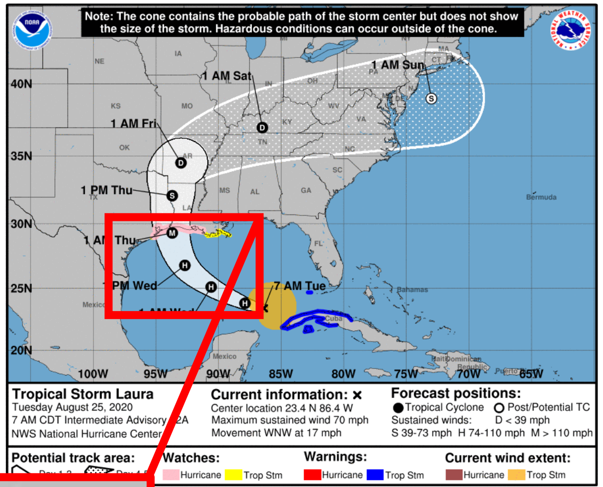
- Rigs and platforms are designed for single use
- We are asking **more** from infrastructure
- Operations in offshore environments introduce hazards that can impact **infrastructure integrity**
- Need methods & models to assess existing infrastructure for **future use (EOR, CS)**

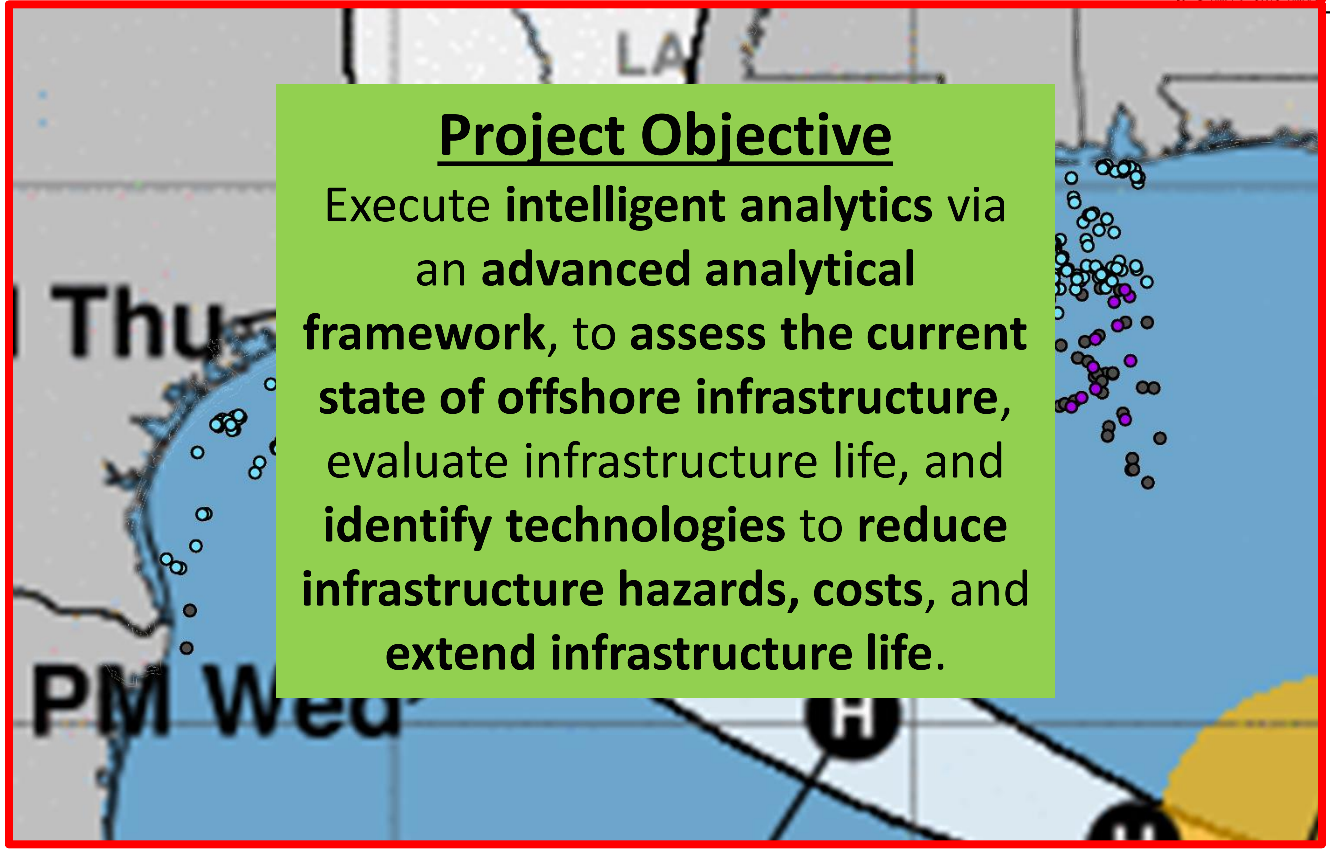


Spectrum News (https://www.baynews9.com/fl/tampa/weather/2020/08/21/only-in-2020--the-gulf-of-mexico-could-have-two-simultaneous-hurricanes-next-week)

Hurricanes Marco & Laura

August 2020





Project Objective

Execute **intelligent analytics** via an **advanced analytical framework**, to **assess the current state of offshore infrastructure**, evaluate infrastructure life, and **identify technologies** to **reduce infrastructure hazards, costs**, and **extend infrastructure life**.

Environmental conditions are getting ***more severe***, ***need to prepare to prevent*** spills but also ***support response planning***

Existing Platforms

as of February 2019

- Fixed
- Mobile
- Unknown

Approach & Results thus Far

- Build **comprehensive dataset**
- Perform **data-driven analytics** to evaluate infrastructure **integrity**
  1. ***Remaining lifespan***
  2. ***Likelihood of future risk***
- Apply **data-driven advanced spatial, statistical, and Machine Learning (ML) models** to **quantify existing infrastructure integrity**
- Release data and models through a **smart, online platform** hosted by **Energy Data eXchange (EDX)**

Energy Data eXchange


Taylor Energy oil platform, destroyed in 2004 during Hurricane Ivan, is still leaking in Gulf

Meteorological & Oceanographic (MetOcean) impacts


fuelfix

Offshore drilling regulator warns of bolt failures in Gulf of Mexico

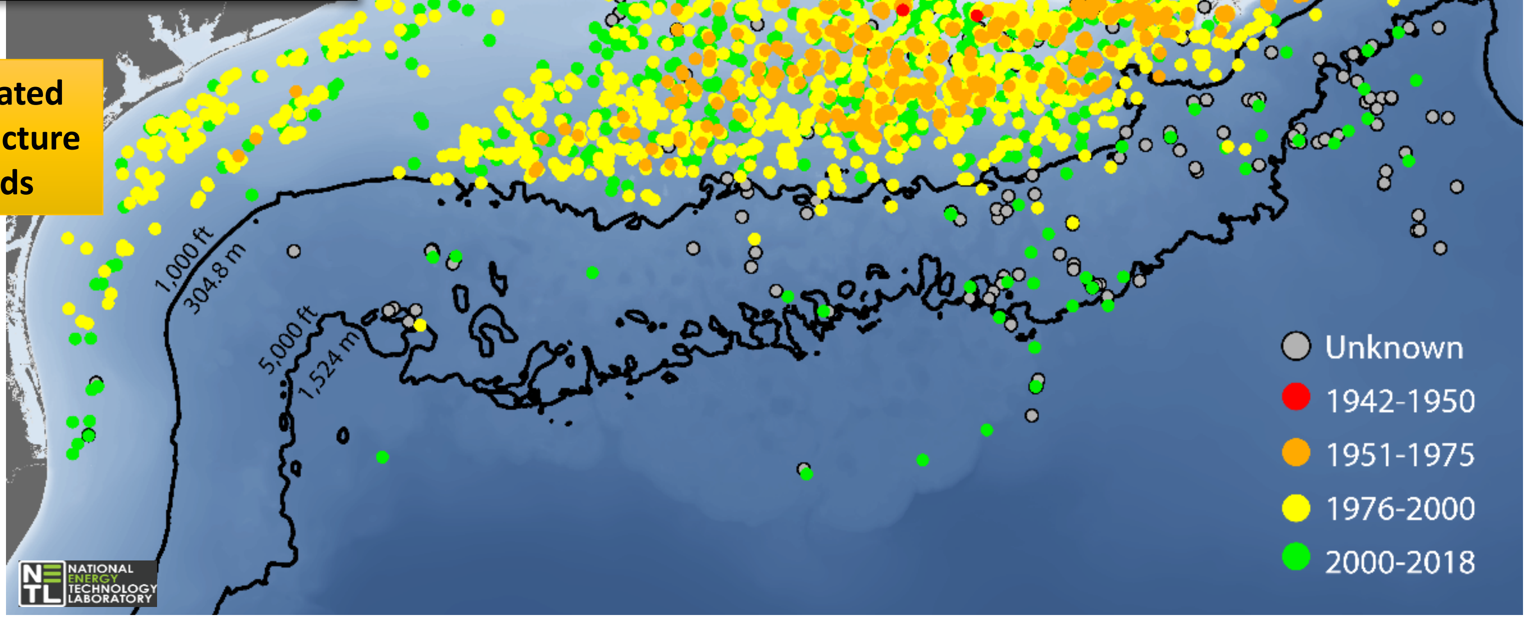
Posted by James Osborne Date: May 03, 2016

Integrity risks

Age-related infrastructure hazards

Values Delivered

- **Identify & address critical hazards**
- **Reduce infrastructure hazards, costs**
- Identify potential for **extending infrastructure life for EOR**

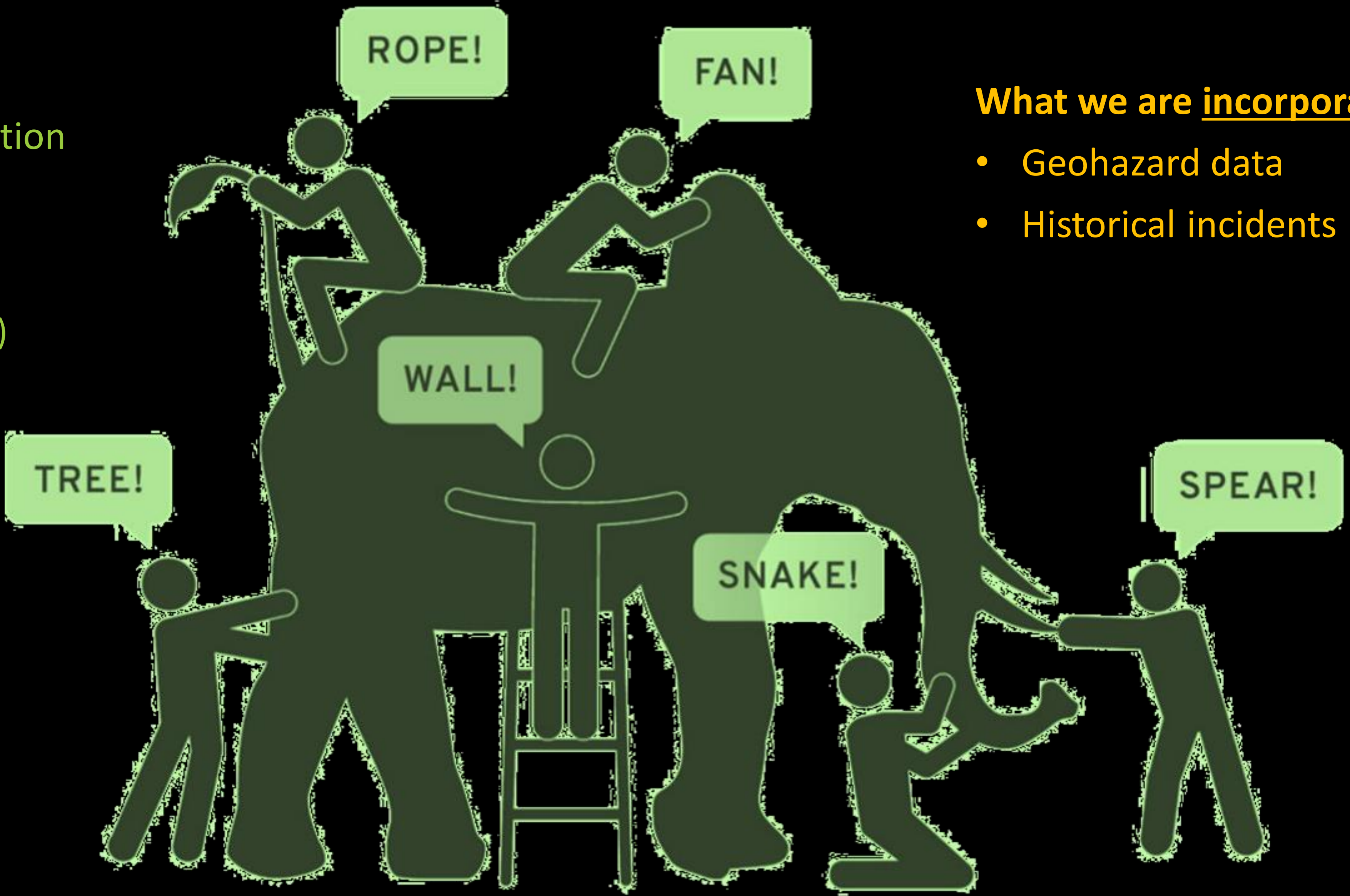


Data-Driven Approach & Driving Insights

*Leveraging **Big Data** & **Big Data Computing** of the whole to inform the local*

What we have:

- Structural information
- Incident records
- MetOcean data (Meteorological & Oceanographic data)



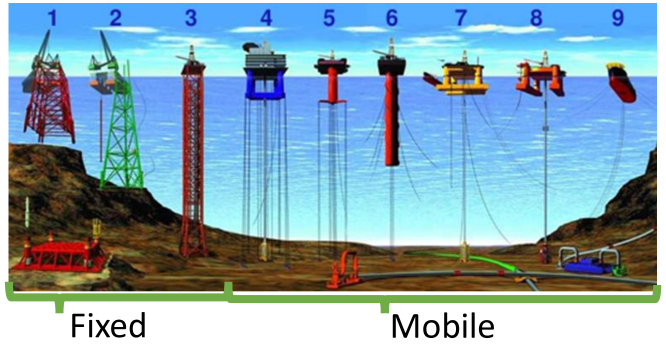
What we are incorporating:

- Geohazard data
- Historical incidents

Dataset Development

- Dataset includes:
  - Structural information
  - Structural- or weather-related incidents
  - Local environment history and anomalies
- Evaluated **existing infrastructure integrity** based on:
  - Location
  - Use
  - Design
  - Operating condition
  - Incident history

Initial analytics focusing on platforms:

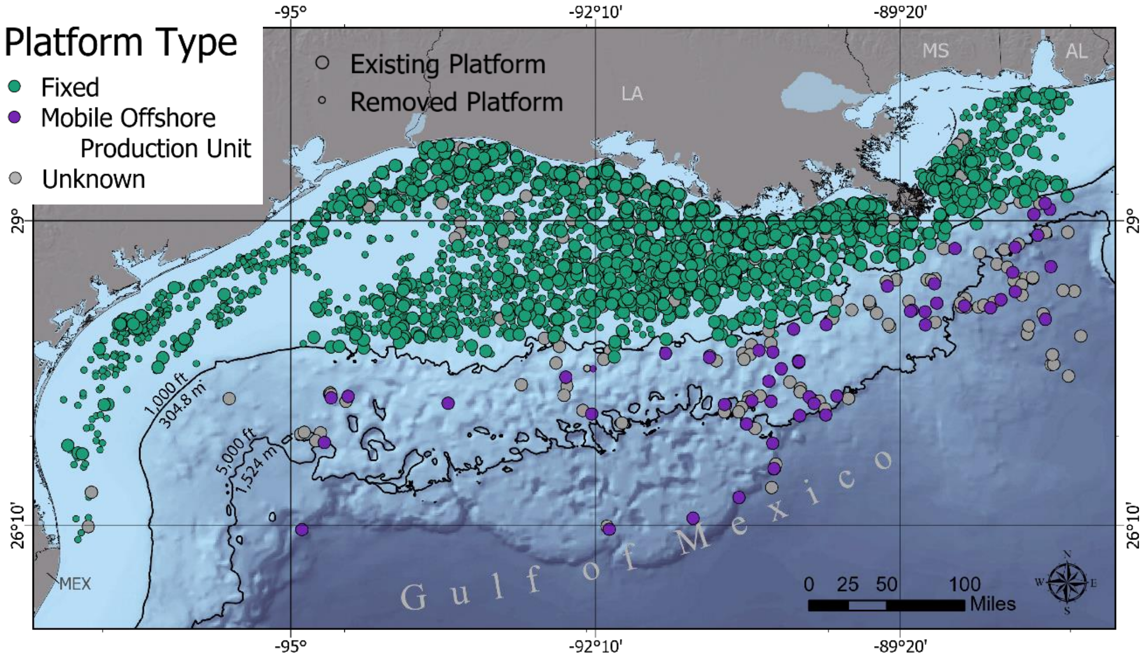


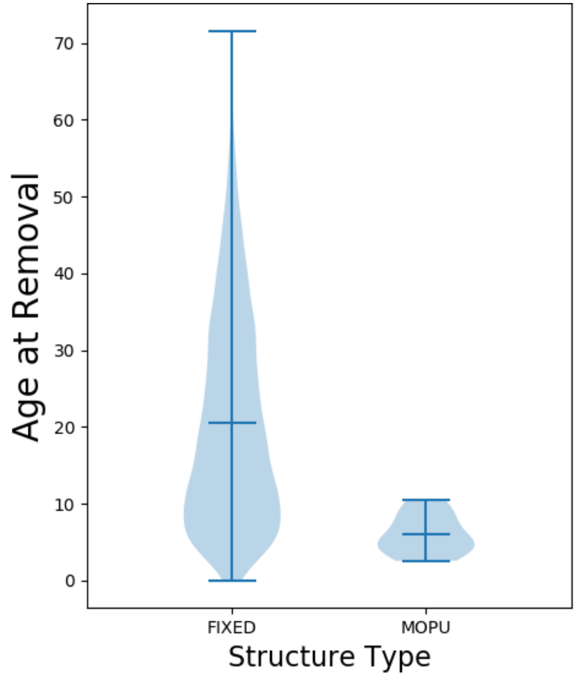
Sources:
BOEMRE, BSEE, USCG, MMS

7,065 platform records
1942-2020

>4,000 incident records
1956-2000, 2006-2018

		FIXED Platforms (FIXED, CAIS, WP, CT)	MOPU Platforms (MOPU, SPAR, MTLP, SSTMP, SEMI)
Existing	Count	1,736	50
	Avg. Current Age (yrs)	35.6	14.5
Removed	Count	5,271	8
	Avg. Age at Removal (yrs)	20.6	6.5
	Std. Dev. Of Age at Removal (yrs)	13.4	2.5
	Max. Age at Removal (yrs)	71.6	10.5
	Min. Age at Removal (yrs)	0	2.6





***228 records missing key information

MetOcean Data Extraction

>51,000 layers (**>130 GB**)

Sources include NOAA, US Navy, World Ocean Database, and external models

HYCOM GOMu0.04 GOMl0.04

- Water velocity

WAVEWATCH III

- Wave height
- Wave direction
- Wave power
- Wind speed

IBTrACS Storms

- Storm characteristics

Proxies for corrosion

- Nitrate
- Temperature
- Dissolved oxygen
- Silicate
- Phosphate
- Salinity

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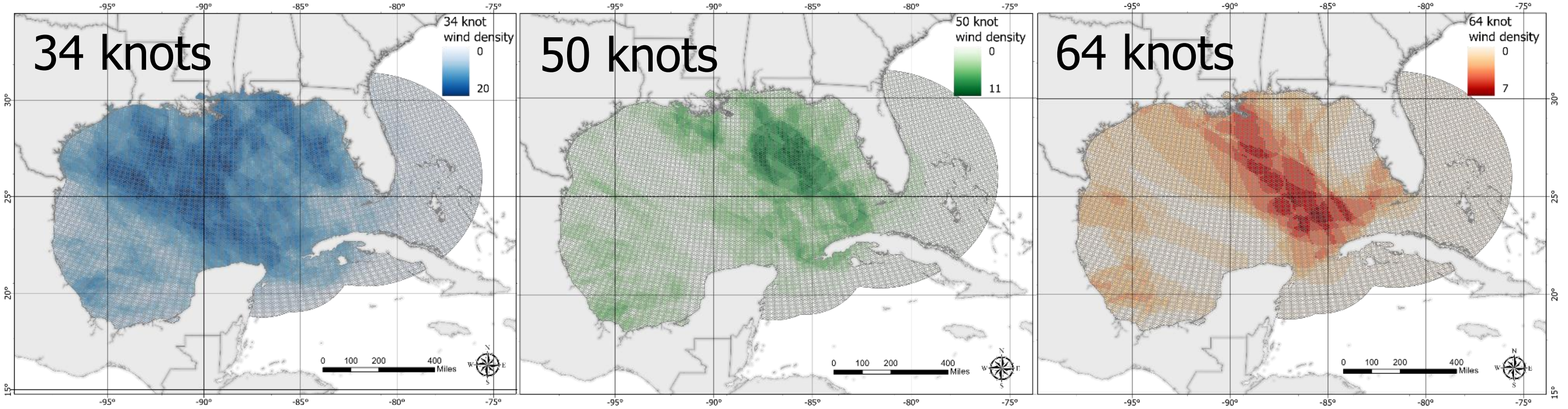
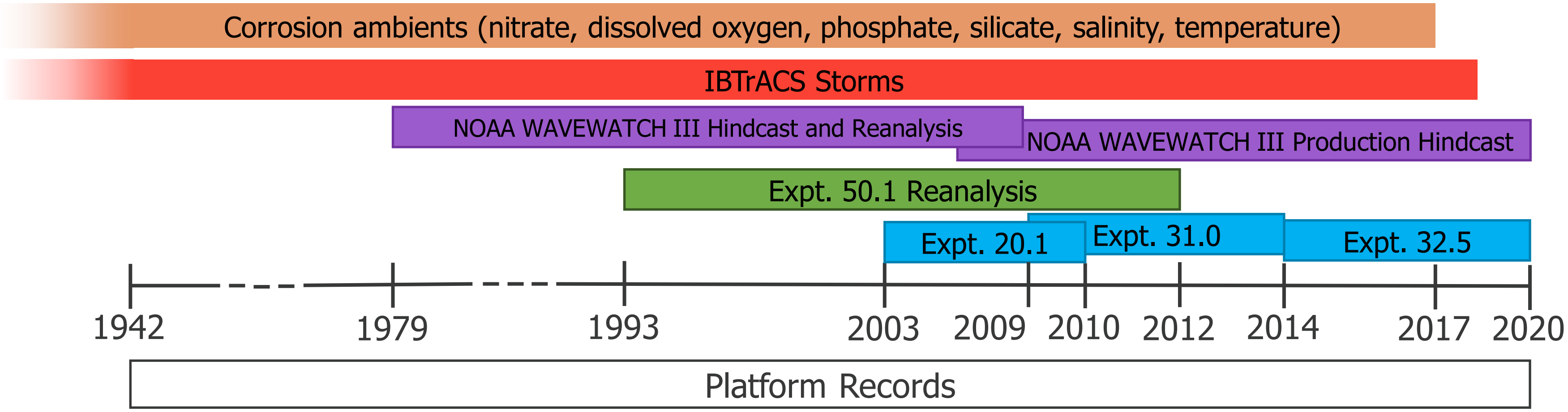
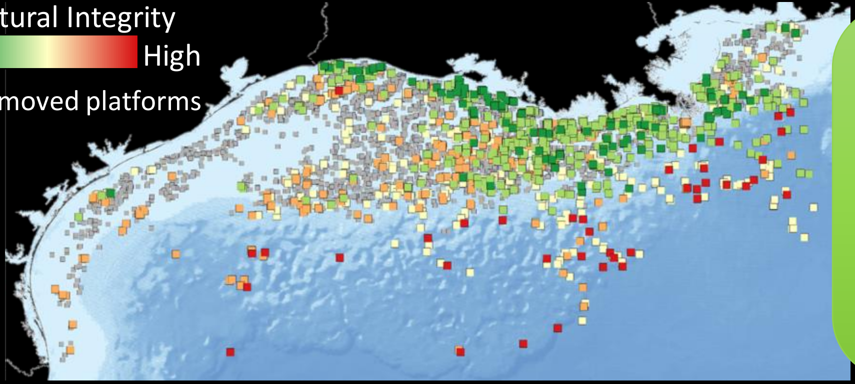
Data example: *Density of storm occurrences by wind speed*





Exploratory Stats & Variable Analyses

- Key variable selection improved understanding of ***operational platform integrity***
- Platforms in areas of more severe environmental conditions are ***removed on average 8 years sooner*** than platforms in less severe areas (Spatial autoregressive model)
- Applied **AIC** for **model quality testing** on > 40 variables



Exploratory statistics & literature found **relationships** between platform age, incident severity, structural complexity, & MetOcean variables

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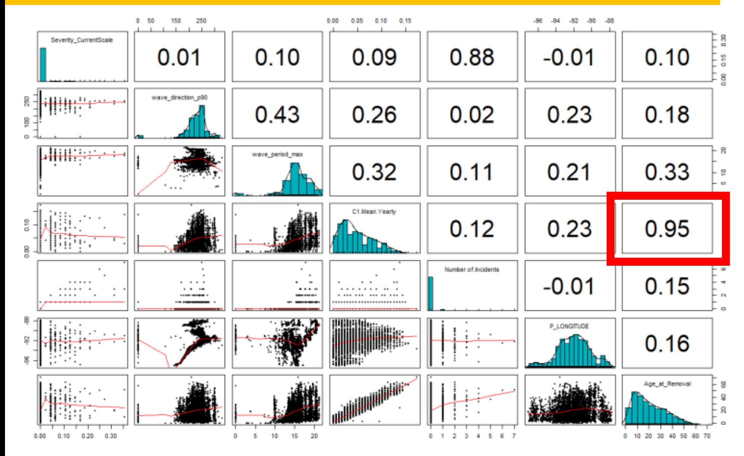
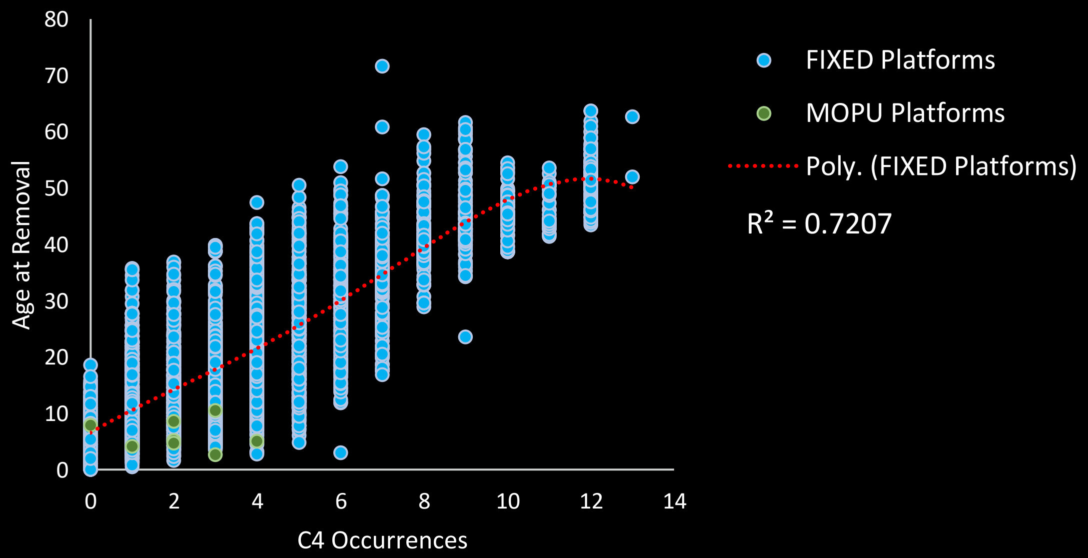
Nelson, J., Dyer, A., Duran, R., Romeo, L., Sabbatino, M., Wenzlick, M., Wingo, P., Zaengle, D., and J. Bauer. *In preparation*. Evaluating Offshore Infrastructure Integrity. NETL-PUB XXX; NETL Technical Report Series; U.S. Department of Energy, National Energy Technology Laboratory: Albany, OR.

Strong relationship (0.95) between hurricanes and removal age (Pearson's Correlation)



C4 Occurrences at Removed Platforms



Potential plateau in the number of times a platform can sustain extreme hurricane conditions (Ordinary Least Squares regression)

Machine Learning & Advanced Algorithms

Applied **multiple methods** with **comprehensive dataset** to model existing platform integrity:

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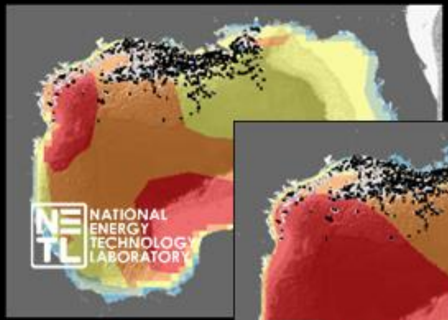
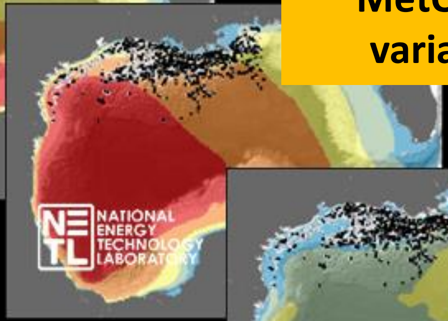
- ***Predicting Lifespan***
  1. Gradient Boosted Classifier
  2. Artificial Neural Network (NN) Classifier
  3. Geographically Weighted Regression
- ***Assessing Risk Likelihood***
  1. Gradient Boosted Regression
  2. NN Regression

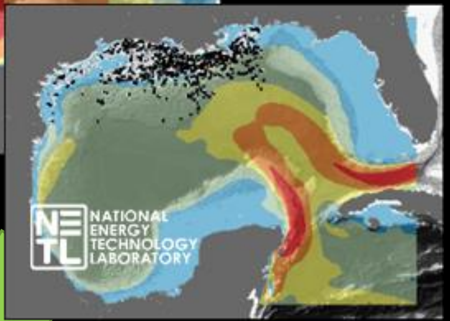
Structural- & weather-related incidents



Wind Speed



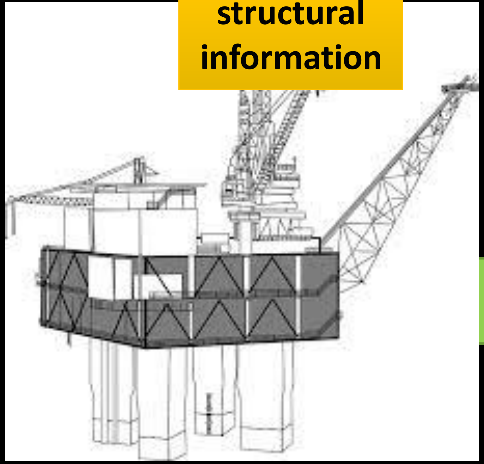
Wave Height



Current Velocity

MetOcean variables

Publicly available structural information



Analyses through ML & advanced statistical models

With new information, **model predictions improve**

https://edx.netl.doe.gov/offshore/portfolio-items/assessing-current-and-future-infrastructure-hazards/

Benefit of Multiple Models

1. Evaluated available data
2. Identified key parameters
3. Assessed multiple approaches
4. Compare results for internal model validation

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Gradient Boosting

Stagewise additive ML model that optimizes model loss by adding weak learners (i.e. decision trees)

Strengths

- Handles outliers and able to perform when data is missing

Limitations

- Difficult to scale model
- Requires careful tuning of parameters

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NN

Deep learning ML model where data are passed through multiple layers that learn weights and biases, which are combined and transformed to learn the phenomena being modeled.

Strengths

- Handles complex and non-linear relationships

Limitations

- Easy to overfit
- Difficult to interpret
- Many parameters to tune

Shared strengths (Gradient Boosting and NN):

- Handles categorical and continuous variables
- Can be used for classification and regression

Geographically Weighted Regression

Spatial model that fits regression equations to each feature (platform), based on dependent and explanatory variables of other local features

Strengths

- Captures local variation in spatial data
- Can be used for prediction

Limitations

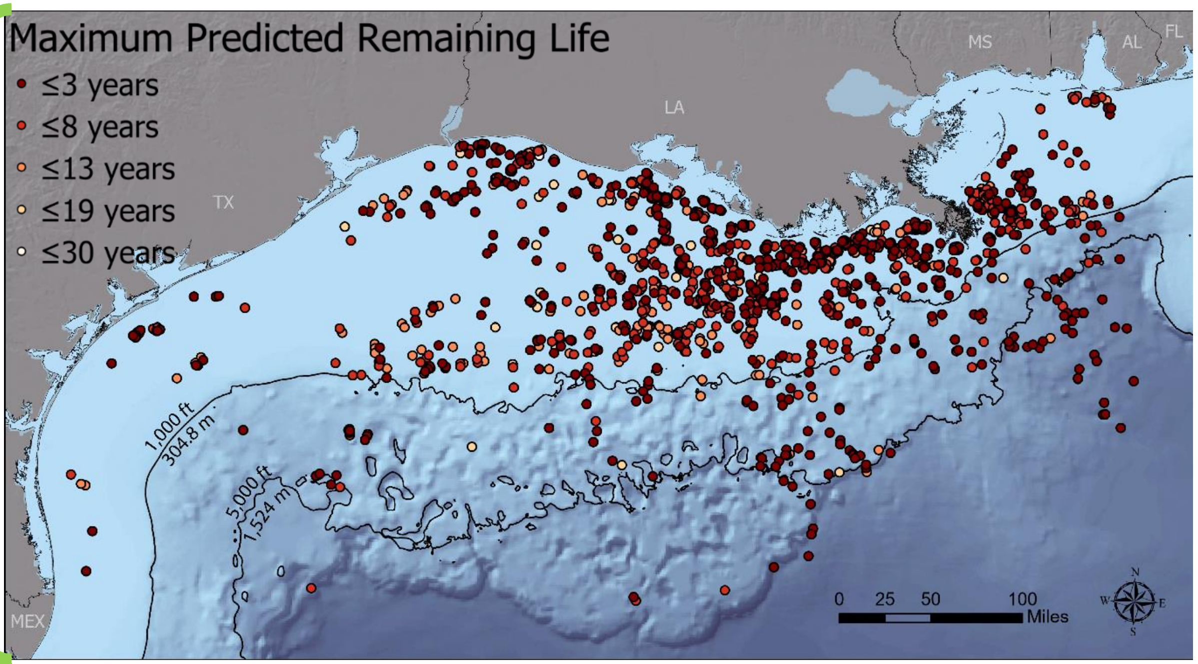
- Computational overhead increases with data volume
- Local collinearity must be considered
- Assumes linear relationships

- Models are only as good as the data going into them

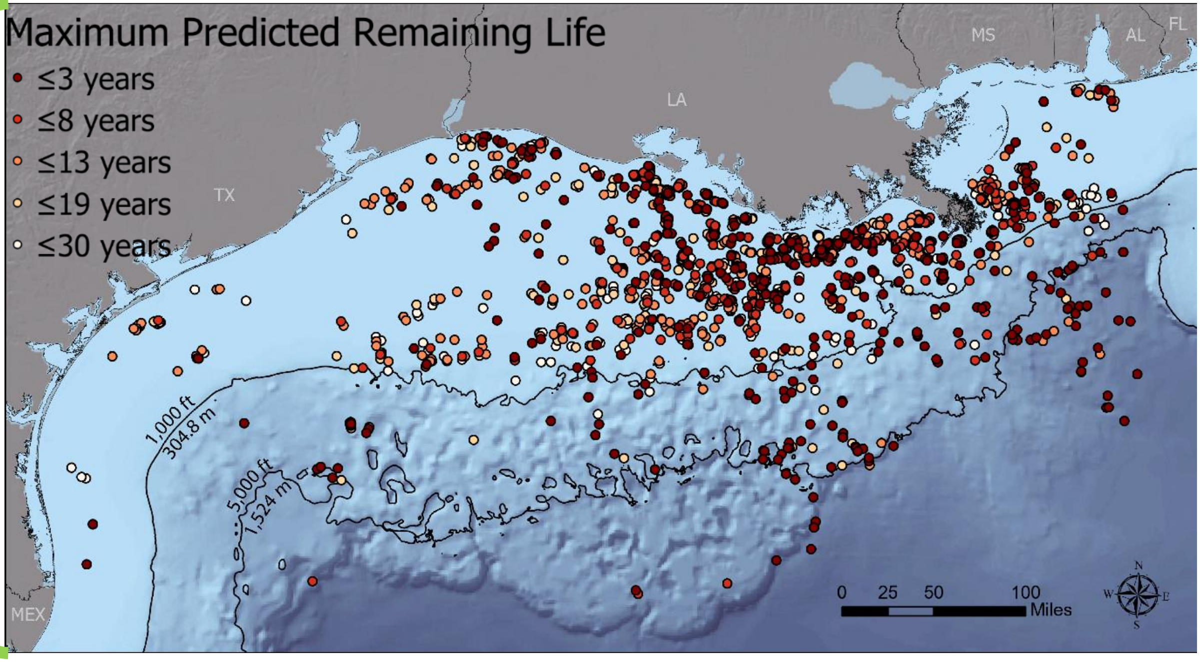
https://edx.netl.doe.gov/offshore/portfolio-items/assessing-current-and-future-infrastructure-hazards/

Predicting remaining lifespan

Gradient Boosted Classification
85-89% accuracy



Artificial Neural Network Classification
81-86% accuracy



$$\text{Accuracy} = \frac{\textit{Correct Predictions}}{\textit{Total Predictions}}$$

Running ***multiple models*** allows us to better understand and ***internally validate results***

Accuracy will increase by giving the model **more accurate information** to learn from

Geographically Weighted Regression

Predicting current age based on health & environment of existing infrastructure

0.85 correlation between known and predicted age

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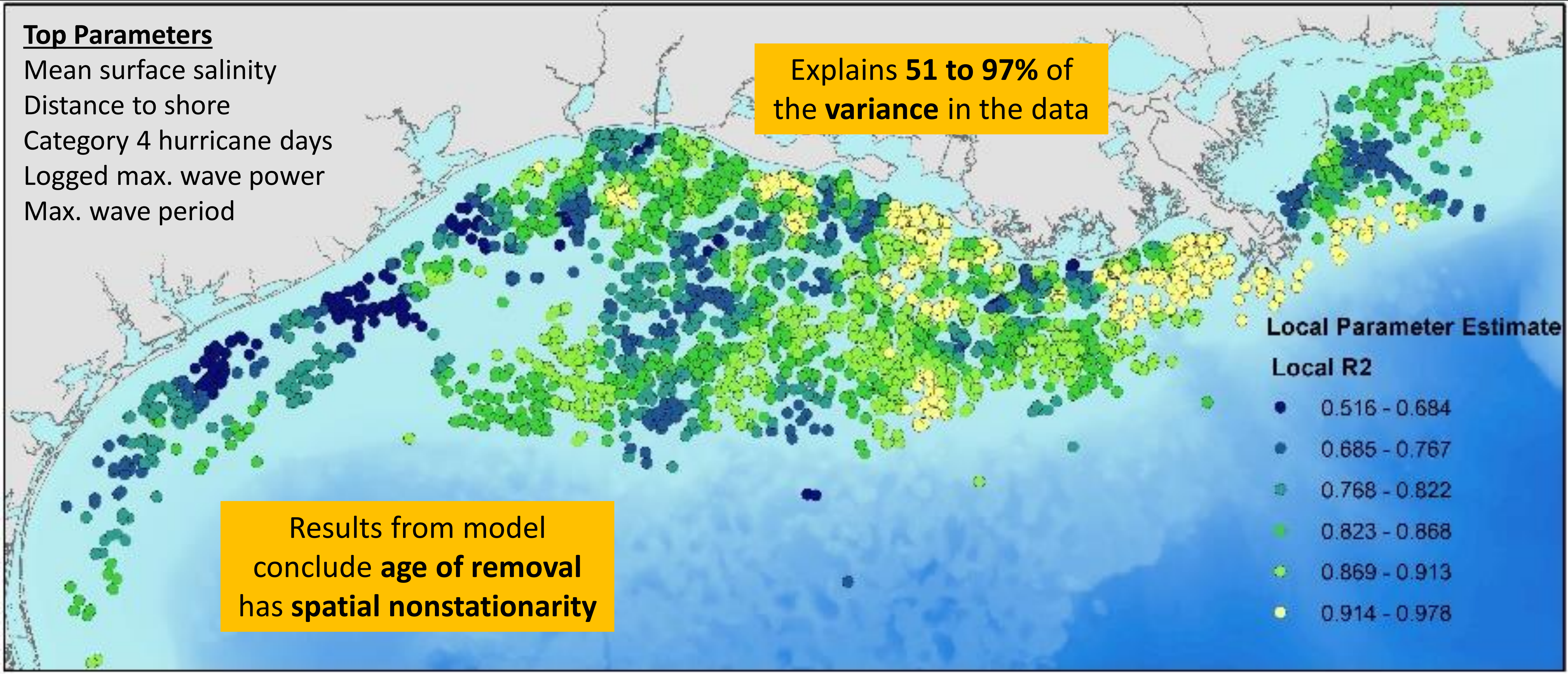
Top Parameters

Mean surface salinity
Distance to shore
Category 4 hurricane days
Logged max. wave power
Max. wave period

Explains **51 to 97%** of the **variance** in the data

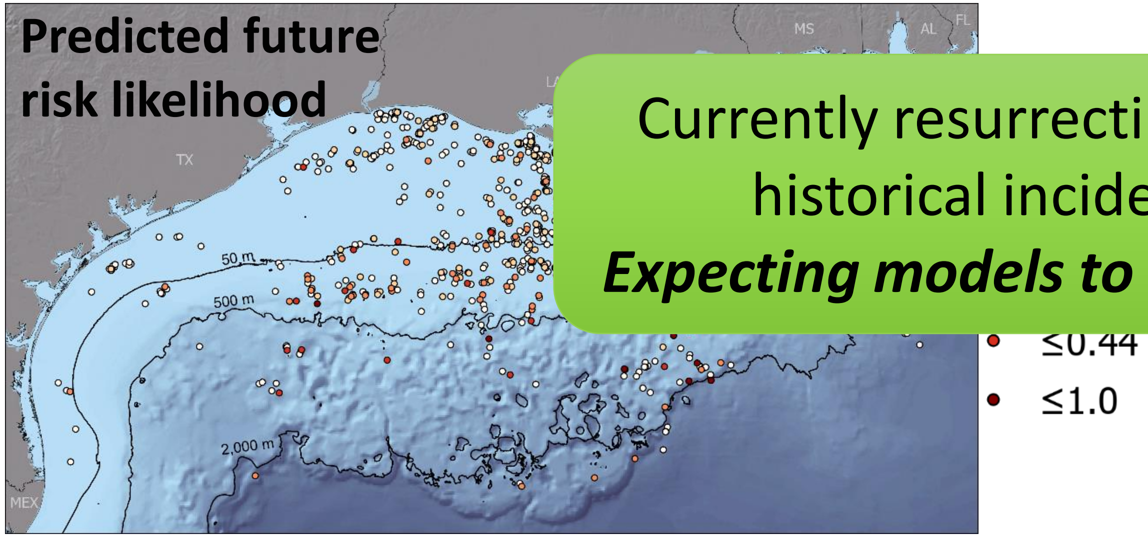


Results from model conclude **age of removal** has **spatial nonstationarity**

Example: Comparing results from two methods
Analyzing risk likelihood with regression with incident severity

Gradient Boosted Regression

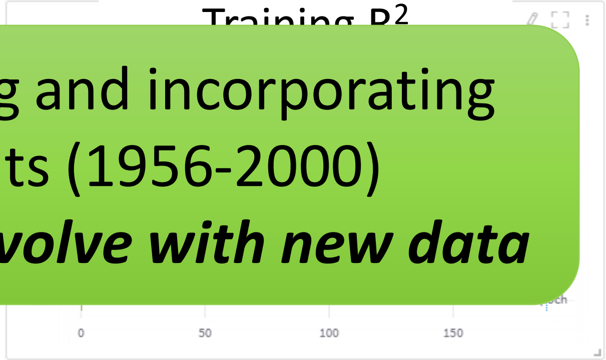
- **85-99% accuracy**, based on cross-validation method with 5 folds to evaluate average model performance

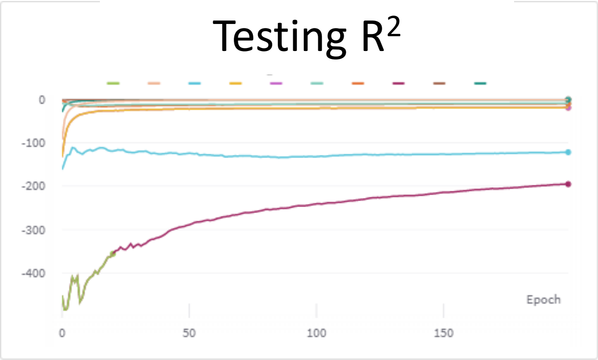


Top Parameters
- Number of structural incidents
- Number of incidents
- Number of incidents during production operations
- Number of electrical incidents
- Category 5 storm (number of days)
- Maximum wind velocity
- Wave height (25th percentile)
- Maximum reported wind gust
- Wind magnitude (50th percentile)
- Number of incidents during motor vessel operations

NN Regression

- Negative accuracy – Anticipating better fitting model with additional data and hyper tuning





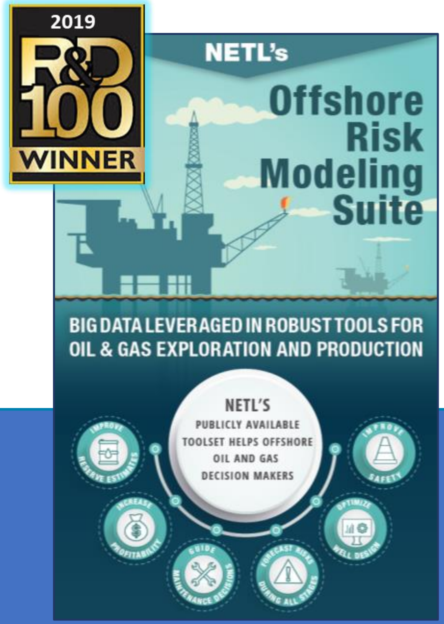
Top Parameters
- Major structure flag (6 completions or >2 pieces of production equipment)
- Water production flag (producing water during inspection)
- Attended 8 hour flag (personnel on board 8 hours per day)
- Quarters type
- Major complex flag (platform contains at least 1 major structure)
- Injection code (injecting gas or water)
- Commingling production
- Allocation Meter flag (platform has allocation meter)
- Production Equipment Flag (installed production equipment)
- Authority status

Currently resurrecting and incorporating historical incidents (1956-2000)

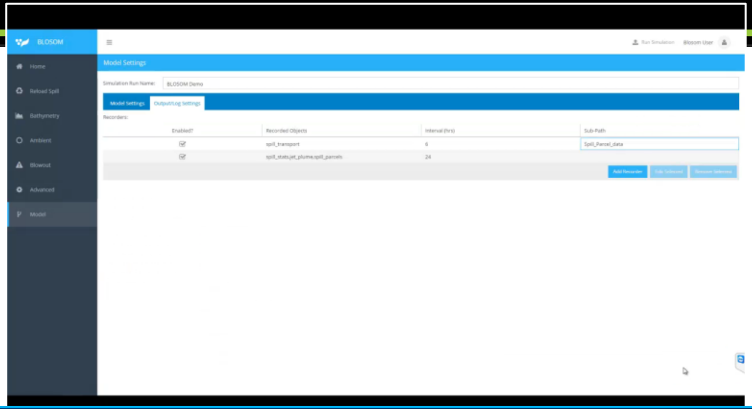
Expecting models to evolve with new data

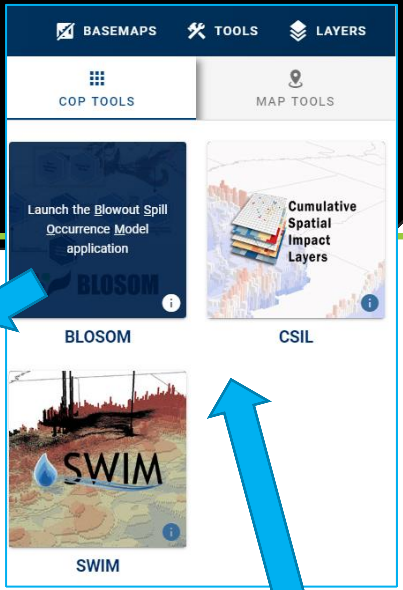
Increasing Access to Data & Models

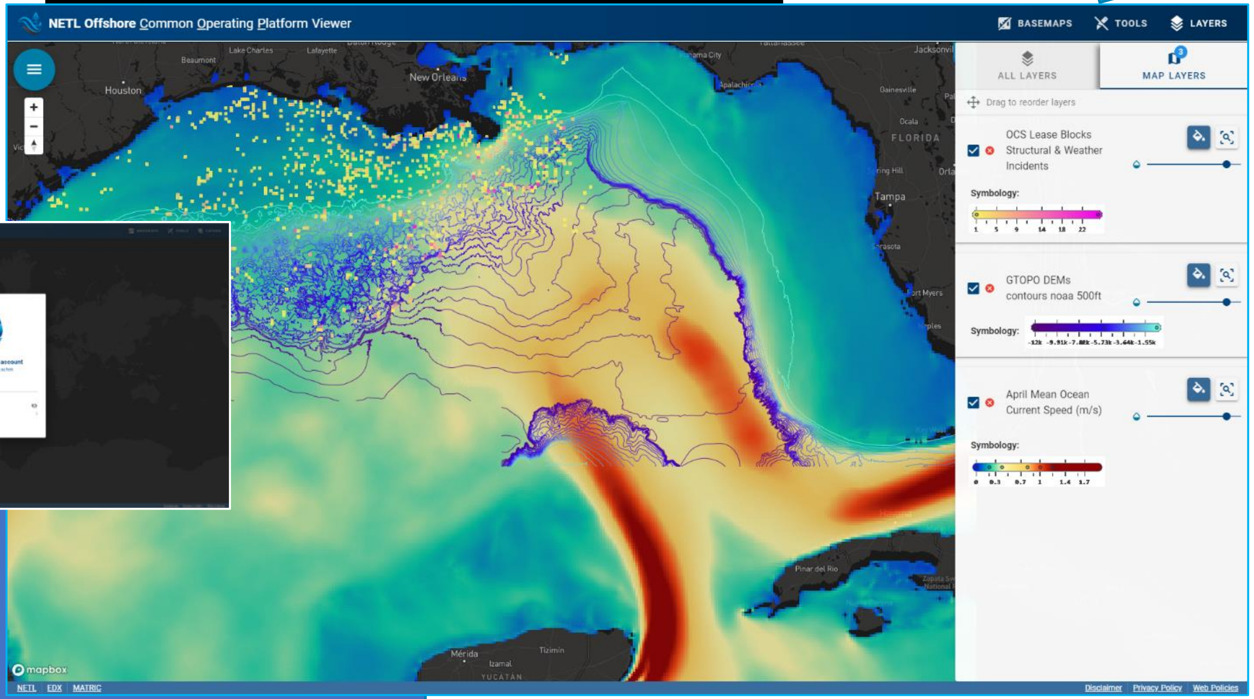
Through NETL's Energy Data eXchange (EDX)



- Integrate **ML, big data, and analytical outputs** with **online platform**
- Leverage **award-winning Offshore Risk Modeling Suite**
- Transform models into online tools to perform **real-time analyses** to **better understand offshore infrastructure integrity**
- Release tools and platform through **EDX**

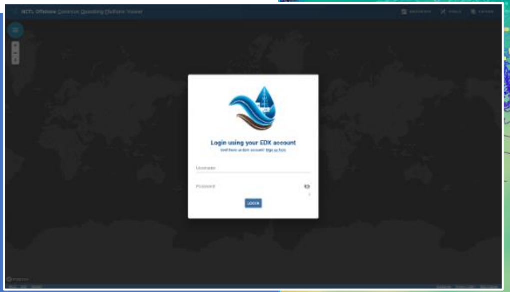






Creation of an online platform for industry, and other stakeholders to access data, tools, and analytical outputs

EDX® Energy Data eXchange



Initial release via EDX for select members of DOE/NETL community at end of EY20

Intelligent Offshore Infrastructure Integrity Analyses

Timeline (present to March 2021)

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Upcoming Milestones		
Date	**Description**	**Status**
12/20	Draft promotional items for upcoming release of online advanced infrastructure analytical platform, Version 2.	On track
02/21	Submit article on intelligent analytics for infrastructure hazards and development.	On track

Upcoming Deliverables		
Date	**Description**	**Status**
12/20	Submit technical report detailing development of intelligent analytics.	On track
03/21	Advanced release of online interactive analytical platform via EDX.	On track

Next steps

- Complete filling data gaps
- Refine & validate models
- Publish technical report on data and methods (Nelson et al., *in progress*)
- Full integration with ORM
- **Release data & models via online platform for real-time prediction & integrity assessments**
- **Publish model comparison manuscript (Dyer et al., *in progress*)**

Publications & Presentations
Upcoming & Past

Upcoming Publications

- Nelson, J., Dyer, A., Romeo, L., Bauer, J., Wenzlick, M., Barkhurst, A., Wingo, P., Sabbatino, M. Evaluating Offshore Infrastructure Integrity. NETL-PUB-XXX; NETL Technical Report Series; U.S. Department of Energy, National Energy Technology Laboratory: Albany, OR. In preparation.
- Dyer, A., Zaengle, D., Duran, R., Nelson, J., Romeo, L., Sabbatino, M., Wenzlick, M., Wingo, P., Bauer, J., and K. Rose. In preparation. Applied Machine Learning Model Comparison: Predicting Offshore Infrastructure Integrity with Gradient Boosting Algorithms and Neural Networks. Targeting Environmental Science & Technology journal.

Upcoming Presentations

- Mark-Moser, M., Romeo, L., Rose, K., Wingo, P., Duran, R. submitted. Assessment of natural and engineered systems data using machine learning to reduce offshore operational risks. Offshore Technology Conference, 2021. Houston, TX.
- Romeo, L., Dyer, A., Zaengle, D., Nelson, J., Wenzlick, M., Duran, R., Sabbatino, M., Wingo, P., Barkhurst, A., Bauer, J., and Rose, K. Machine Learning Driven Forecasting of Offshore Infrastructure Integrity. in prep. Interagency Coordinating Committee on Oil Pollution Research (ICCOPAR) Quarterly Meeting. December, 2020. Virtual.

Past Presentations

- Justman D., Romeo, L., Barkhurst, A., Bauer, J., Duran, R., Dyer, A., Nelson, J., Sabbatino, M., Wingo, P., Wenzlick, M., Zaengle, D., Rose, K. invited talk. Advanced geospatial analytics and machine learning for offshore and onshore oil & natural gas infrastructure. GIS Week 2020. October 6-7, 2020. Virtual.
- Dyer, A., Romeo, L., Wenzlick, M., Bauer, J., Nelson, J., Duran, R., Zaengle, D., Wingo, P., and Sabbatino, M. *2020*. Building an Analytical Framework to Measure Offshore Infrastructure Integrity, Identify Risk, and Strategize Future Use for Oil and Gas. *Esri User Conference*, San Diego, CA, July 13-15, 2020. https://www.esri.com/en-us/about/events/uc/overview
- Dyer, A., Rose, K., Bauer, J., Romeo, L., Barkhurst, A., Wingo, P., Sabbatino, M., Nelson, J., Wenzlick, M., Building an Analytical Framework to Measure Offshore Infrastructure Integrity, Identify Risk, and Strategize Future Use for Oil and Gas, AGU Ocean Sciences Meeting 2020, Oral Presentation. https://www.agu.org/Ocean-Sciences-Meeting
- Romeo, L. and Barkhurst, A. Building Big Data Geospatial Tools for a Common Operating Platform: Cumulative Spatial Impact Layers. DOE GIS Users Group Meeting. September 10, 2020. Virtual. Invited presentation.
- Romeo, L., Wenzlick, M., Dyer, A., Sabbatino, M., P. Wingo, Nelson, J., Barkhurst, A., Bauer, J., and Rose, K. 2019. Building Data-Driven Analytical Approaches and Tools to Evaluate Offshore Infrastructure Integrity. Addressing the nation’s energy needs through technology innovation – 2019 carbon capture, utilization, storage, and oil and gas technologies integrated review meeting, Pittsburgh, PA, August 26-30, 2019.

Key Takeaways

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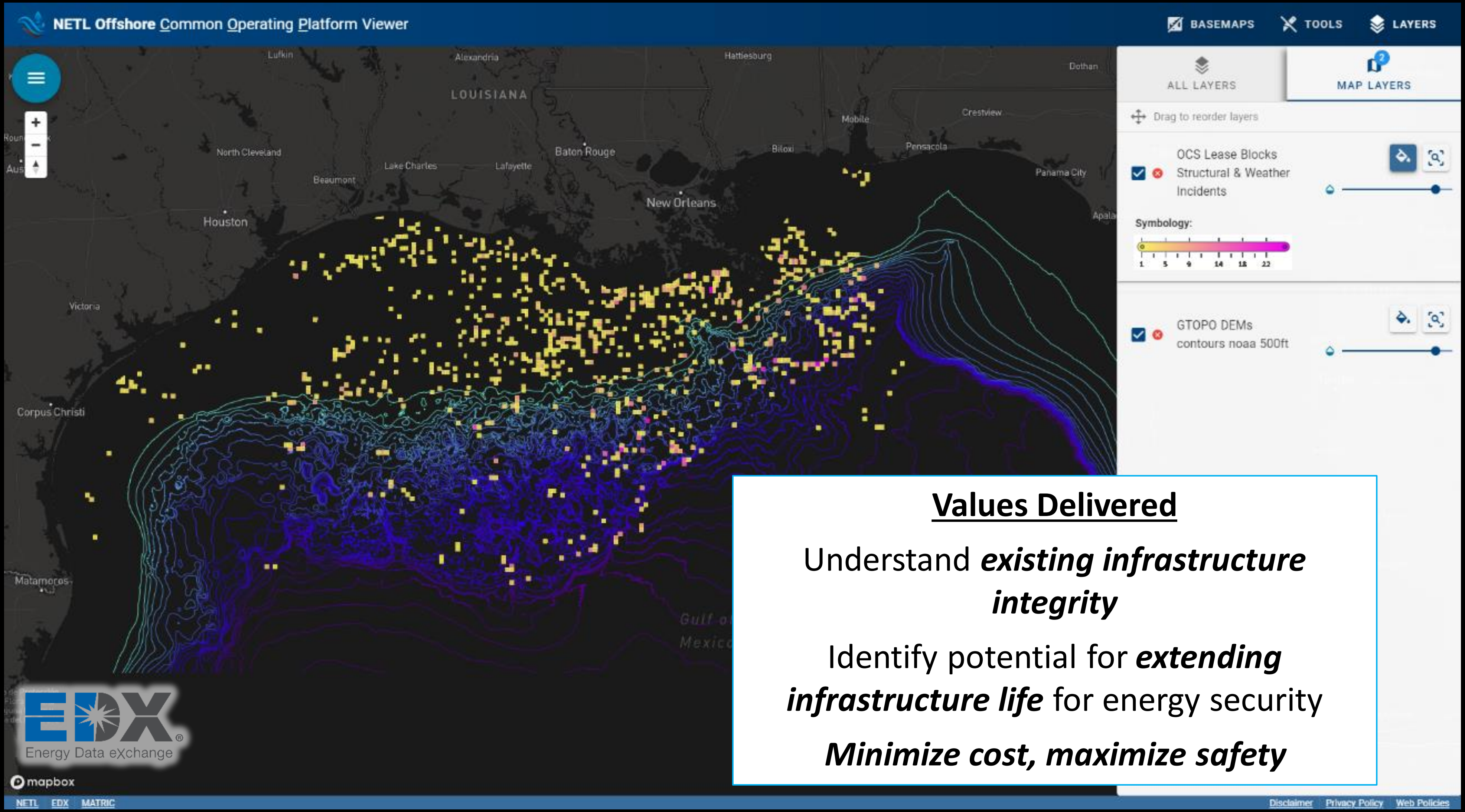
- Built comprehensive infrastructure dataset
- Developed novel ML analytical models to predict existing lifespan and risk
- Continuing to add data to make models smarter
- Pubs are in prep
- Integration of data, models, and tools on virtual platform



Values Delivered

Understand ***existing infrastructure integrity***

Identify potential for ***extending infrastructure life*** for energy security

Minimize cost, maximize safety

https://edx.netl.doe.gov/offshore/portfolio-items/assessing-current-and-future-infrastructure-hazards/

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- **Acknowledgement:** Parts of this technical effort were performed in support of the National Energy Technology Laboratory's ongoing research under the Offshore Unconventional Resources – DE FE-1022409 by NETL's Research and Innovation Center, including work performed by Leidos Research Support Team staff under the RSS contract 89243318CFE000003.